AD-A119 171 PERCEPTRONICS INC WOODLAND HILLS CA F/G 5/10
MENTAL REPRESENTATION OF CIRCUIT DIAGRAMS: INDIVIDUAL DIFFERENC--ETC(U)
JUN 82 T D WICKENS, R E GEISELMAN, M G SAMET N00014-81-C-0590
UNCLASSIFIED PATR-1109-82-6 NL

END
DATE
FILMED
11 82
DTIC

AD A119171

ANNUAL TECHNICAL REPORT PATR-1109-82-6
Contract Number: N00014-81-C-0580
June 1982

MENTAL REPRESENTATION OF CIRCUIT DIAGRAMS: INDIVIDUAL DIFFERENCES IN STRUCTURAL KNOWLEDGE

Thomas D. Wickens
Ralph E. Geiselman
Michael G. Samet
Cynthia L. Yelvington

Prepared for:

OFFICE OF NAVAL RESEARCH
800 North Quincy Street
Arlington, VA 22217

PERCEPTRONICS

6271 VARIEL AVENUE • WOODLAND HILLS • CALIFORNIA 91367 • PHONE (213) 884-7470

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

REPORT DOCUMENTATION PAGE

READ INSTRUCTIONS BEFORE COMPLETING FORM

1. REPORT NUMBER	2. GOVT ACCESSION NO. AD-A119 171	3. RECIPIENT'S CATALOG NUMBER
4. TITLE (and Subtitle) Mental Representation of Circuit Diagrams: Individual Differences in Structural Knowledge		5. TYPE OF REPORT & PERIOD COVERED Annual Report
		6. PERFORMING ORG. REPORT NUMBER PATR-1109-82-6
7. AUTHOR(s) Thomas D. Wickens, Ralph E. Geiselman, Michael G. Samet, & Cynthia L. Yelvington		8. CONTRACT OR GRANT NUMBER(s) N00014-81-C-0590
9. PERFORMING ORGANIZATION NAME AND ADDRESS Perceptronics, Inc. 6271 Variel Avenue Woodland Hills, CA 91367		10. PROGRAM ELEMENT, PROJECT, TASK AREA & WORK UNIT NUMBERS
11. CONTROLLING OFFICE NAME AND ADDRESS Office of Naval Research 800 North Quincy Street Arlington, VA 22217		12. REPORT DATE June 1982
		13. NUMBER OF PAGES 47
14. MONITORING AGENCY NAME & ADDRESS (if different from Controlling Office) Same as Above		15. SECURITY CLASS. (of this report) Unclassified
		15a. DECLASSIFICATION/DOWNGRADING SCHEDULE

16. DISTRIBUTION STATEMENT (of this Report)

Unlimited

17. DISTRIBUTION STATEMENT (of the abstract entered in Block 20, if different from Report)

18. SUPPLEMENTARY NOTES

19. KEY WORDS (Continue on reverse side if necessary and identify by block number)

circuit diagrams, clustering algorithms, cognitive models, electronic circuits, expert systems, functional knowledge, individual differences, knowledge representation, mental representation, ordered trees, structural knowledge, symbolic knowledge

20. ABSTRACT (Continue on reverse side if necessary and identify by block number)

This work is concerned with the knowledge that electronics technicians possess of electronic equipment, and more generally, with how people operate in tasks that draw upon a complex spatial symbolic knowledge base. A technician's knowledge base is postulated to consist of three types of related knowledge: (a) structural/functional knowledge, which pertains to the actual configuration of a circuit and the role that its components play in the operation of the device; (b) prototypical knowledge, which pertains to the general properties common to circuits of a given type; and (c) procedural knowledge, which pertains -

DD FORM 1473, 1 JAN 73 EDITION OF 1 NOV 65 IS OBSOLETE

UNCLASSIFIED

SECURITY CLASSIFICATION OF THIS PAGE (When Data Entered)

to the way that a circuit can be modified and to the interaction among knowledge elements of all three types of knowledge. The first of these knowledge types, structural/functional knowledge, was studied in an experiment in which subjects were asked to reconstruct circuits and to partition circuits into components. Dramatic performance differences, in terms of errors and speed, were found between technicians of varying skill levels. However, any between-group differences in the derived representations of the structural/functional knowledge base were dwarfed by individual differences in the patterns of reconstruction and partitioning performance. Therefore, it is anticipated that more fundamental differences among technicians of varying skill levels lie in their respective procedural knowledge. The results of this research program should help in providing guidelines for training electronic technicians to better understand and troubleshoot complex equipment.

TABLE OF CONTENTS

	Page
INTRODUCTION	1
Nature of Mental Representations	2
Experts and Novices	6
Research Perspective	8
METHOD	9
Materials	9
Procedure	16
Subjects	19
Method of Analysis	20
RESULTS	23
Errors During Acquisition	23
Recall Orders	25
DISCUSSION	41
REFERENCES	45

ABSTRACT

This work is concerned with the knowledge that electronics technicians possess of electronic equipment, and more generally, with how people operate in tasks that draw upon a complex spatial symbolic knowledge base. A technician's knowledge base is postulated to consist of three types of related knowledge: (a) structural/functional knowledge, which pertains to the actual configuration of a circuit and the role that its components play in the operation of the device; (b) prototypical knowledge, which pertains to the general properties common to circuits of a given type; and (c) procedural knowledge, which pertains to the way that a circuit can be modified and to the interaction among knowledge elements of all three types of knowledge. The first of these knowledge types, structural/functional knowledge, was studied in an experiment in which subjects were asked to reconstruct circuits and to partition circuits into components. Dramatic performance differences, in terms of errors and speed, were found between technicians of varying skill levels. However, any between-group differences in the derived representations of the structural/functional knowledge base were dwarfed by individual differences in the patterns of reconstruction and partitioning performance. Therefore, it is anticipated that more fundamental differences among technicians of varying skill levels lie in their respective procedural knowledge. The results of this research program should help in providing guidelines for training electronic technicians to better understand and troubleshoot complex equipment.

INTRODUCTION

The performance of complex tasks such as maintaining mechanical equipment, modifying and adapting computer programs, and troubleshooting sophisticated electronic devices requires highly skilled personnel. Furthermore, all such tasks require that these personnel have a detailed understanding of the devices that are being repaired and maintained. Thus, knowledge about how people mentally represent complex devices is necessary for developing suitable personnel training programs and for designing optimal man-machine interfaces for maintenance equipment.

The training of personnel to troubleshoot electronic circuits has typically been less than successful. In a review of the status of troubleshooting in the military services, Bond and Towne (1979) state:

> The main conclusion of this report...(is that) troubleshooting of very complex systems is difficult for numerous reasons, but the critical factor is that the technician's cognitive map of essential physical relations (electronic, hydraulic, electro-mechnical, and so on) in complex equipment is often incomplete, vague, or incorrect. As long as this is so, any series of checks and test readings, though apparently well motivated and accomplished, cannot 'close in' logically on a faulty unit. (pp. 5-6)

The premise underlying the present research effort is that training programs may be deficient when they fail to provide troubleshooters with the knowledge required to develop a sufficiently rich conceptual structure of the equipment with which they are working. Accordingly, the research presented here is directed toward understanding the nature of the knowledge base that is necessary for the repair and maintenance of complex electronic devices.

Nature of Mental Representations

Troubleshooting entails the isolation and repair of malfunctioning components in a device and, as such, is a form of problem solving. It may be analyzed in terms of problem solving theories (see, e.g., Greeno, 1978, for a review). Presumably, the problem-solving procedures operate on a substrate of knowledge, which includes a mental representation of a device. This underlying structure must be established before problem-solving theories can be applied.

It is apparent that an expert's mental representation of a complex device is not isomorphic to a schematic drawing of the device. In fact, mental representations contain much more information than the schematic itself. (See Brown, Collins, & Harris, 1978, for a similar point of view.) For example, an expert readily can identify functional units within a circuit that are not directly present in the diagram. Therefore, a prudent initial stage of research is to model the latent knowledge and the cognitive mechnisms that allow the expert to develop an enriched mental representation from a schematic drawing.

The mental representation is composed of a number of interrelated and overlapping structures. These structures may be hierarchical in form, although this is not crucial. The hierarchical character arises from the tendency to view several components of an electronic device as a unit, without examining their fine structure unless necessary. For example, one may think of a logic-circuit component as a flip-flop, without analyzing it into basic components unless forced to do so. This hierarchical tendency has been supported in modern integrated circuits by the physical modularization of rather complex functions in single chips or modules; in computers, for example, CPUs, interface units, and various hardware drivers are packaged as single units.

The overlapping nature of the representation results from the fact that a particular component participates in several organizations at once. In some computer designs, for example, a circuit representing the fourth bit of an accumulator may logically be analyzed as part of that accumulator, or may be considered as part of the array of fourth bits over a series of registers such as the accumulator, program counter, etc. (It is interesting that both forms of organization are reflected in the physical design of different computers.) As a more prosaic example, an electric fuel pump in an automobile participates in both the electrical system and the fuel system of the car. Presumably all of these overlapping organizations are accessible to the subject; which is employed at a particular time depends on the dictates of the task. The processing demands that the subject places on the mental representation enables one form or the other.

Thus, the cognitive representation of information given in a circuit diagram may be usefully described as a set of parallel networks. In part, these networks have a hierarchical structure, in that the terminal nodes represent individual circuit components (resisters, capacitors, etc.), the intermediate nodes represent either functional units (rectifiers, amplifiers, etc.) or physically proximal collections of components, and the highest nodes represent the total circuit (a power supply, an inverter, etc.).

Clearly, particular tasks use knowledge in different ways. Although the range of uses forms a complex and multidimensional space, a good case can be made for classifying knowledge about a complicated mechanism (such as a circuit diagram) into three general classes. The definitions of these classes follows.

Structural and Functional Knowledge. Knowledge of this type deals with the way in which a device in constructed and the role that its parts play in the operation. One may know, for example, that a transformer serves to change the voltage of an AC supply, that a particular combination of transitors acts as a flip-flop, and so forth. Fundamentally, this knowledge is static; it describes the way that the device is put together and how it works. Information of this type is easiest to model as some form of connected network (Anderson, 1976; Anderson & Bower, 1973; Collins & Loftus, 1975; Norman & Rumelhart, 1975; Schank, 1972). In such a model, individual circuit components would be represented by nodes in the network and the interrelationships among components, by links between the nodes. In their basic form, representations of this sort are isomorphic to the actual circuit diagrams. At a higher level, they also permit abstract nodes to represent the hierarchical relationship among functional groupings of components. Most of the work with these models has been done in building and testing theories of the organization of long-term memory and thus has been outside the context of problem-solving tasks. An exception is the work of Bhaskar and Simon (1977) who have undertaken an analysis of the structure of long-term memory used by students solving problems in a college-level course in chemical-engineering thermodynamics.

Prototypical Knowledge. Devices are not understood in isolation, but are related to other devices. Prototypical knowledge relates one device to more general prototypes. For example, experienced technicians are able to quickly recognize that several different circuit diagrams represent the same class of device. This suggests a set of procedures that force the constituent elements of a circuit diagram into prototypical configurations. One portion of a circuit is a rectifier, another a Schmitt trigger, etc. Two cognitive processes seem to be involved here. First, some form of bottom-up mechanism simplifies the representation of

the diagram by replacing groups of nodes with a single node. Second, a top-down mechanism attempts to fill in missing nodes in partially matched prototypes. Prototypical knowledge does not consist of an exact memory for a particular circuit; instead it emphasizes the common elements and patterns across a range of devices. Since the operation of any device is related to to an abstracted prototype, the mental burden of the structural and functional facts is greatly reduced.

Procedural Knowledge. Many tasks require more than a static comprehension of a device, demanding that some modification be made or some operation be performed on it. The knowledge necessary to do this is different from the other two types, embodying a series of procedures (algorithmic or heuristic) for changing the device. Procedural knowledge is the most complex of the three types of knowledge, and draws heavily on the others.

Because of its *active representation*, procedural knowledge has been found most useful in simulation (e.g., Winograd, 1972) and problem solving models (Newell & Simon, 1972); and some models (e.g., Anderson, 1976) have incorporated procedural and other forms of representation as well. DeKleer (1979) and deKleer and Brown (1980) have described, from an artificial intelligence point of view, some of the procedural strategies that are required to analyze the operation of a circuit. In particular, they emphasize the need for multiple procedural strategies. For example, DeKleer (1979) hypothesizes that people use topological, functional, and geometric representations. In topological analysis, the topology of a new circuit is compared to that of previously recognized circuits; in functional analysis, the behavior of the indivdual components; and geometric analysis relies on the tacit graphical language engineers use when they describe circuit topologies on paper. These representations are used to analyze a circuit in terms of its "teleolo-

gy." Similarly, Stevens and Collins (1980) argue that people maintain multiple representations of physical systems such as those that determine the rainfall.

Experts and Novices

Previous work relevant to understanding how people represent complex equipment from schematic drawings comes from research comparing the performance of experts to that of novices. Considerable research in this area has indicated that experts differ from novices more in perceptual-memorial abilities than in logical, problem-solving abilities. If it were simply the case that experts know more about the task than novices, there wou'd be little to be gained from constructing an elaborate representation of the task. However, this seems not to be the case. Experts appear to have representations that differ qualitatively from those of novices, and studies supporting this position are becoming more common.

For example, Egan and Schwartz (1979) demonstrated that expert electronic troubleshooters have a richer mental representation of circuit information than novice troubleshooters, and in reconstruction, the experts recall the diagrams in groupings of functional units. The skilled technician's advantage in this task did not hold for non-meaningfully arranged symbols.

Work by deGroot (1966), Chase and Simon (1973), and Simon and Chase (1973), comparing the performance of Master and weaker chess players, indicates that Masters do not "see" ahead further than the weaker players. Instead, the Masters are superior to weaker players in their ability to perform tasks involving the recall of actual chess positions. The superior performance of Masters in these tasks cannot be attributed

to generally superior visual short-term memory capacities of the Masters because when hess pieces are placed randomly on the board, recall is equally poor for Masters and weaker players.

Badre (1979) has found similar results for the recall of battlefield situation displays. Military experts show a marked advantage over novices for plausible situation displays, but not for randomly arranged positions. Furthermore, military experts recall battlefield units on the basis of their functional relationship to each other. Similar results hold for other spatial tasks, such as the recall of GO positions (Reitman, 1976), and have also been extended to other non-spatial tasks such as the recall of computer programs (Reitman, McKeithen, Reuter, & Hirtle, 1979) and the solution of physics problems (Chi, Feltovich, & Glaser, 1979; Larkin, 1979; Larkin, McDermott, Simon, & Simon, 1980).

The most appealing theoretical explanation of these findings is that experts perceive spatial stimuli by coding the stimuli into groups consisting of several elements or chunks. In one version of this theory (Simon & Gilmartin, 1973), the chunks have verbal labels that can be retained in short-term memory and decoded at the time of recall. It is argued that experts quickly represent an entire spatial configuration in a relatively small number of chunk labels and that these labels can be used to reconstruct the spatial configuration. Pauses between successively recalled elements, the estimated size and number of chunks, and the correspondence of recall groupings in copying tasks support this hypothesis.

However, the difference between experts and novices may lie as much or more in the ability of experts to draw from a larger collection of operations--or procedural knowledge--than in an understanding of the structural and functional nature of the parts of the task or in the

reference to prototypes. Much previous work has ignored the dynamic, procedural aspects of complex tasks in favor of more static conceptualizations.

Research Perspective

Reviews of the literature on the mental representation of tasks or stimuli reveal that the derived representations are surprisingly well matched to the task. This suggests that a person is able to adopt a mental representation that is closely concordant with local processing demands. The true mental representation must have latent in it a variety of possible forms and structures. Consequently, any analysis of the mental characteristics of a domain of knowledge must derive from a variety of tasks and must posit a variety of individual representations. Also, the understanding of skilled performance in tasks such as circuit analysis requires consideration of multiple domains of knowledge. That is, different domains are necessary to explain the richness of an expert troubleshooter's mental constructs, and a comprehensive model must incorporate elements of each domain.

The experiment reported here was designed to assess the structural and functional knowledge of electronic devices possessed by technicians varying in skill level. This work provides the necessary background for the future investigation of procedural knowledge as related to electronic trouble-shooting. The experiment performed was a composite of a circuit-reconstruction task and a circuit-partitioning task.

METHOD

Materials

Three circuit diagrams were extracted from manuals of Navy electronic equipment for use in the experiment. Each diagram was sufficiently large to represent several separate subsections and to contain enough nodes to have a reasonably complex internal structure. The diagrams were selected to represent three levels of complexity.

The small circuit, which contains 25 component parts, is shown in Figure 1. This circuit consists of a simple two-stage amplifier for a video signal. It contains two amplifier stages, centered on the two transistors with their associated circuitry. There is a single supply voltage, V_{CC}. This circuit was used with the less skilled subjects only.

The medium-sized circuit, which contains 32 component parts, is shown in Figure 2. This circuit, which is part of a radio receiver, generates a radio frequency signal, and then mixes (i.e., heterodynes) it with another signal that enters from the previous stages on the input line. The RF signal is generated by an oscillator, composed primarily of the transistor and a crystal. This signal is coupled through a transformer to the mixer itself. The combined result is fed to the next stage of the receiver. A single 16-volt supply powers the circuit. This circuit was used with all subjects.

The large circuit is presented in Figure 3. This circuit consists of the final audio stages of a radio receiver and contains 84 component parts. The signal from the radio's discriminator enters to the audio preamplifier. It passes from there through a low-pass filter to remove high-frequency noise, then through the final power amplifier to the

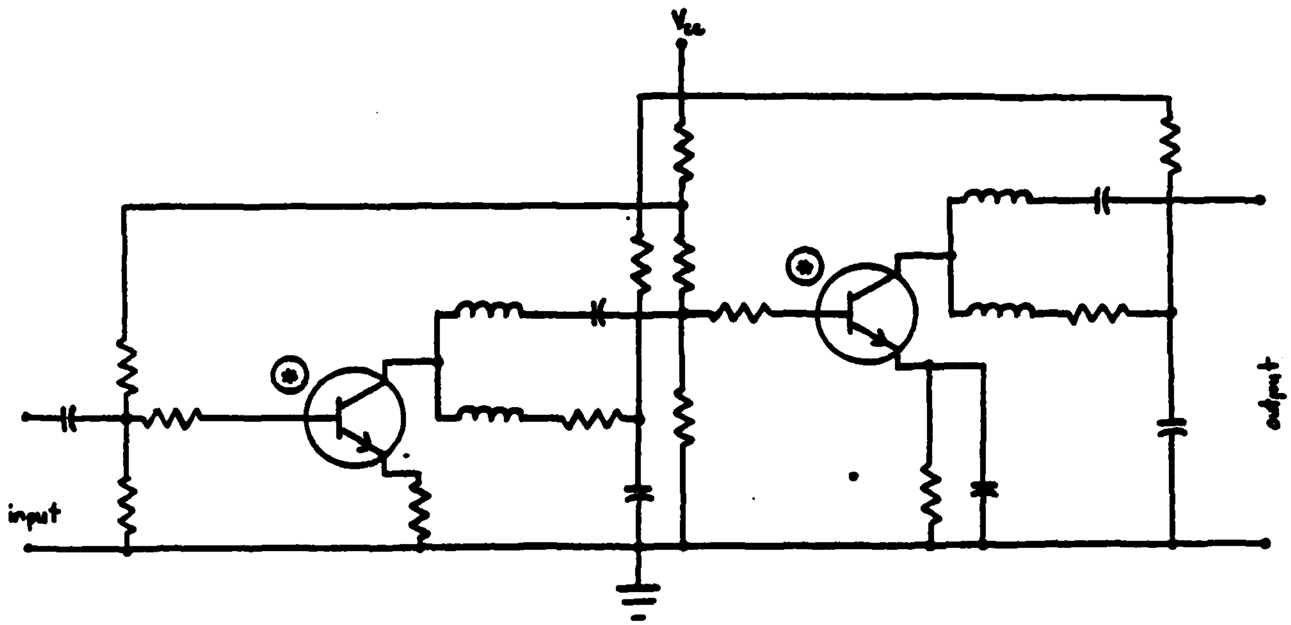

FIGURE 1.
THE SMALL CIRCUIT (THE ASTERISKS
DENOTE THE TWO CUE POSITIONS).

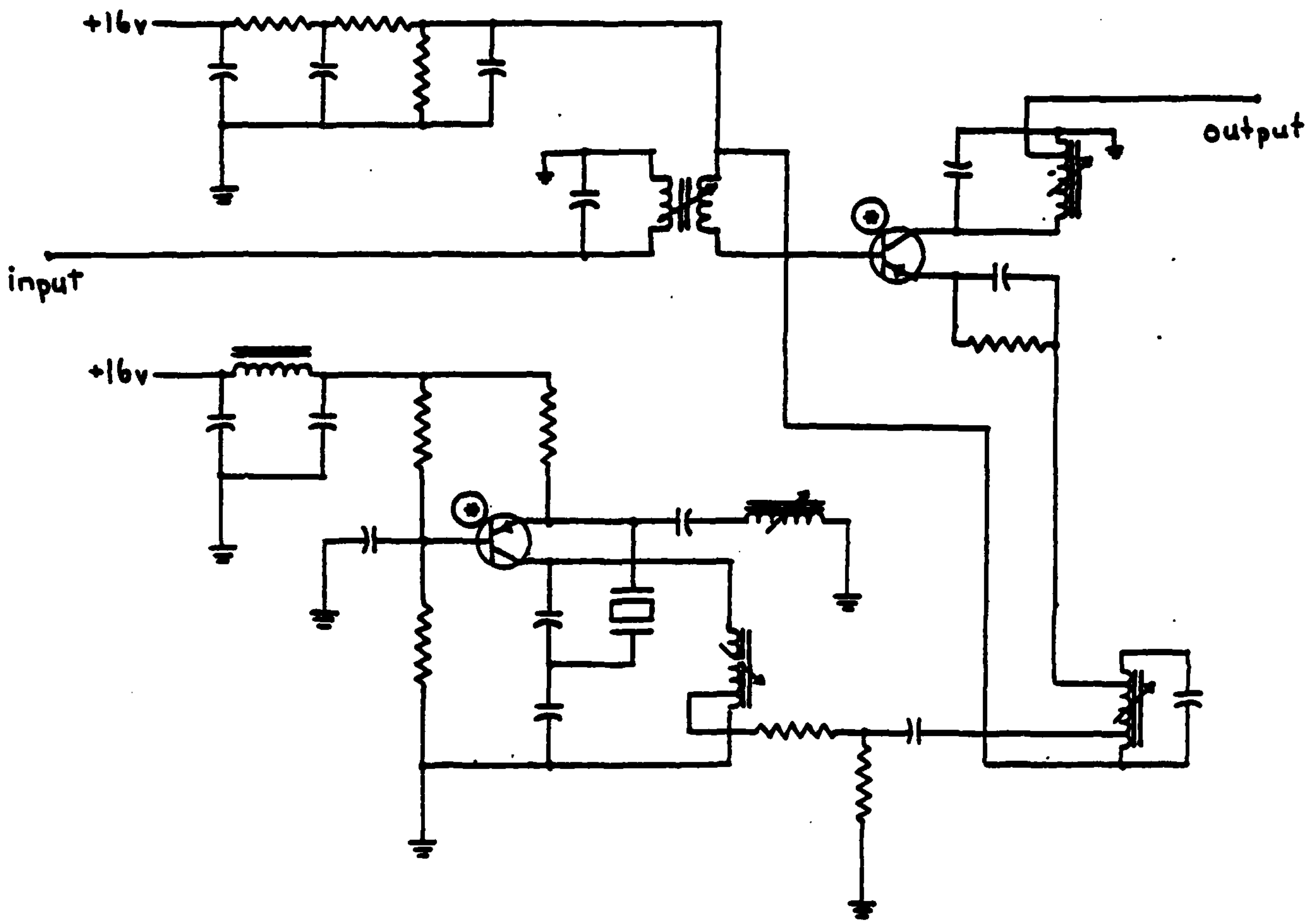

FIGURE 2.
THE MEDIUM-SIZED CIRCUIT (THE ASTERISKS DENOTE THE TWO CUE POSITIONS).

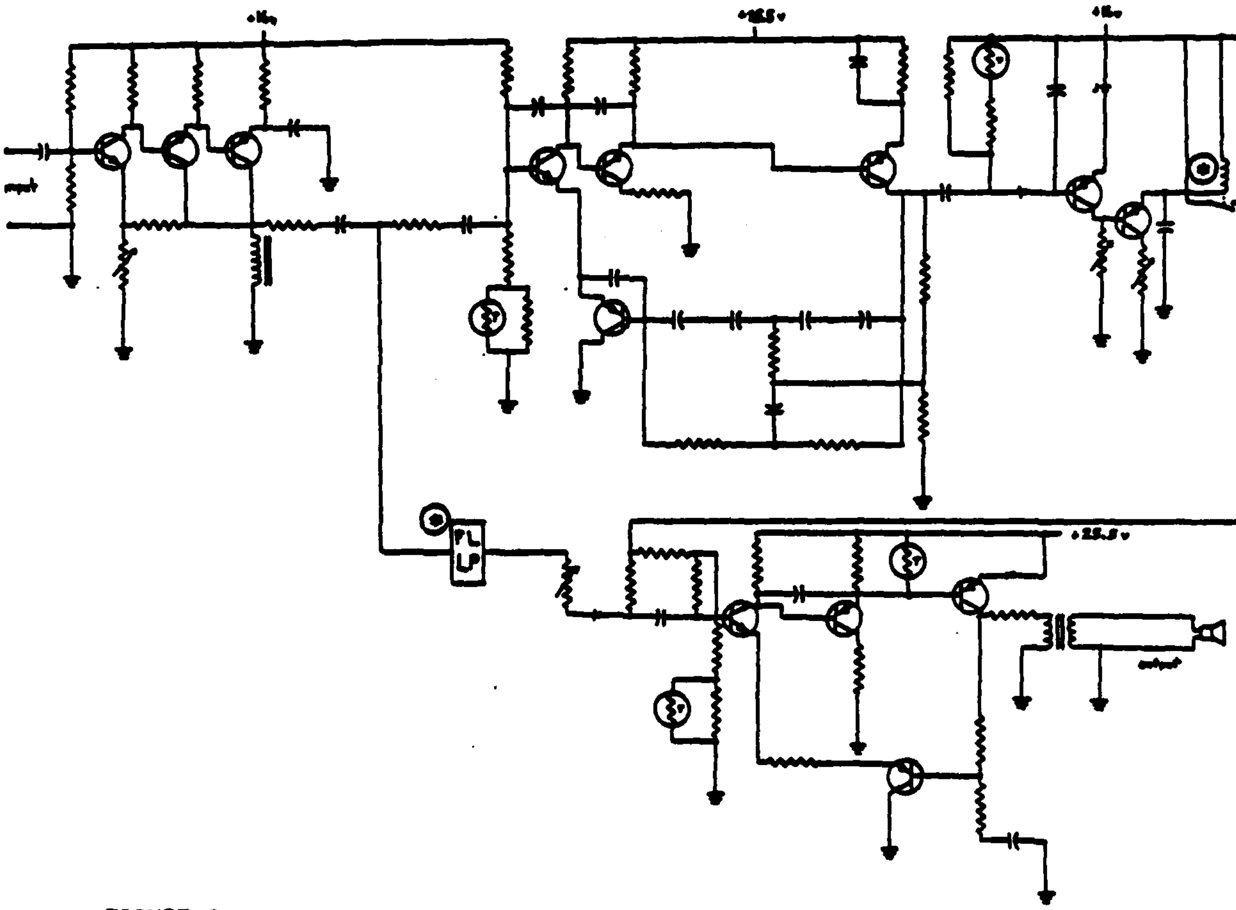

FIGURE 3.
THE LARGE CIRCUIT (THE ASTERISKS DENOTE THE TWO CUE POSITIONS).

speaker. At the same time, the unfiltered signal is fed to another amplifier that contains a feedback network, to make it maximally sensitive to interstation noise. In the presence of this noise, the signal is rectified and amplified to throw the squelch relay, disabling the signal to the power amplifier and suppressing the output. There are two power supply voltges for the circuit, with positive voltages of 16 and 25.5 volts. This circuit was used only with the expert subjects.

Each diagram was prepared in five configurations and three formats. The five configurations of each diagram differed only in the layout on the page. Use of these different configurations throughout the experiment was to prevent the subject from learning only properties of the diagram specific to the physical layout of the diagram. The three formats were constructed giving successively less and less information about the particular components while constraining the basic orientation of the circuit. The formats were (1) the complete diagram as in Figures 1, 2, and 3; (2) a diagram showing interconnections in which the particular components have been replaced by black dots; and (3) a diagram showing only the connections, but lacking specific indications of where the components are located. Examples of the reduced formats, for the configuration of the medium-sized circuit shown in Figure 2 are given in Figures 4 and 5. Note that both the power-supply voltages and the ground points are still shown in these figures. These points were not part of either the reconstruction or the recall task.

Each of the diagrams was drawn on a piece of paper roughly 2' x 3', such that they could then be placed on a magnetic board of the same size. Magnetized components matching the components on the diagram were constructed at about 3/4" in size.

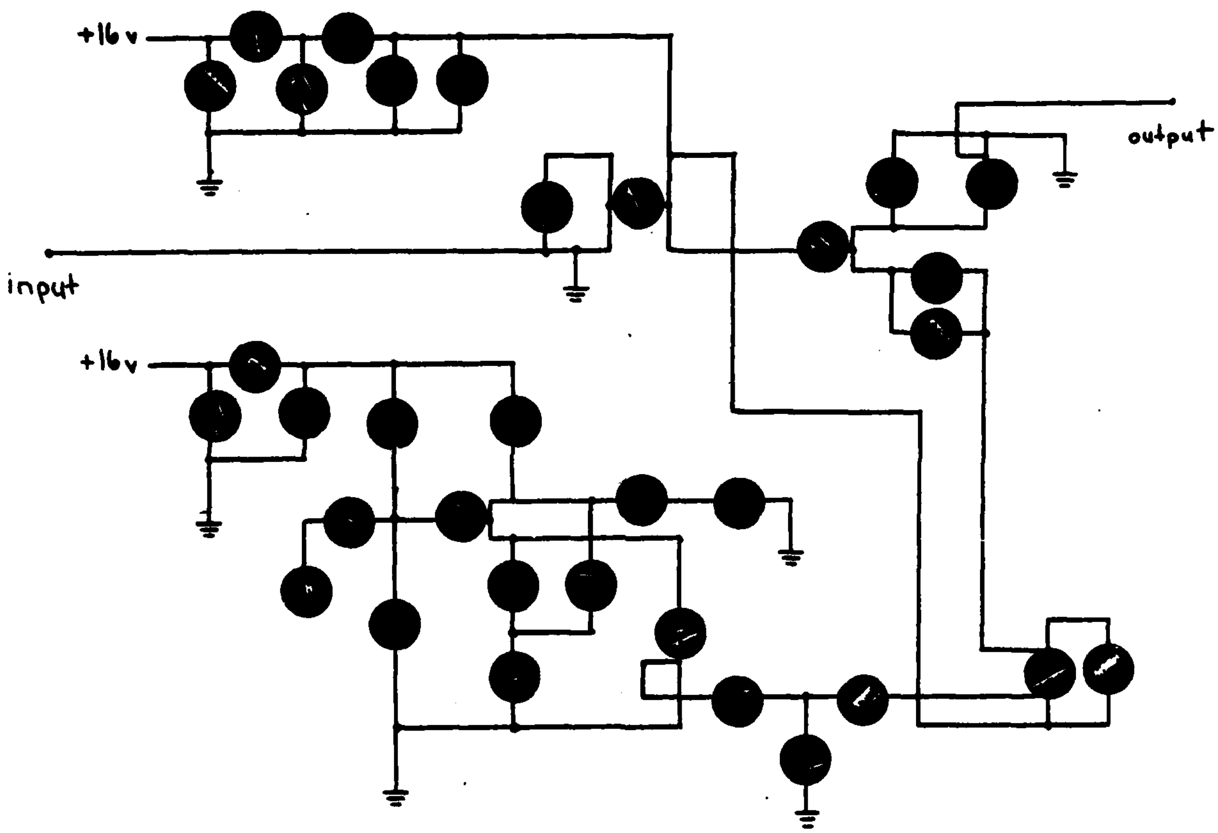

FIGURE 4.
THE MEDIUM-SIZED CIRCUIT OF FIGURE 2
(DOT FORMAT).

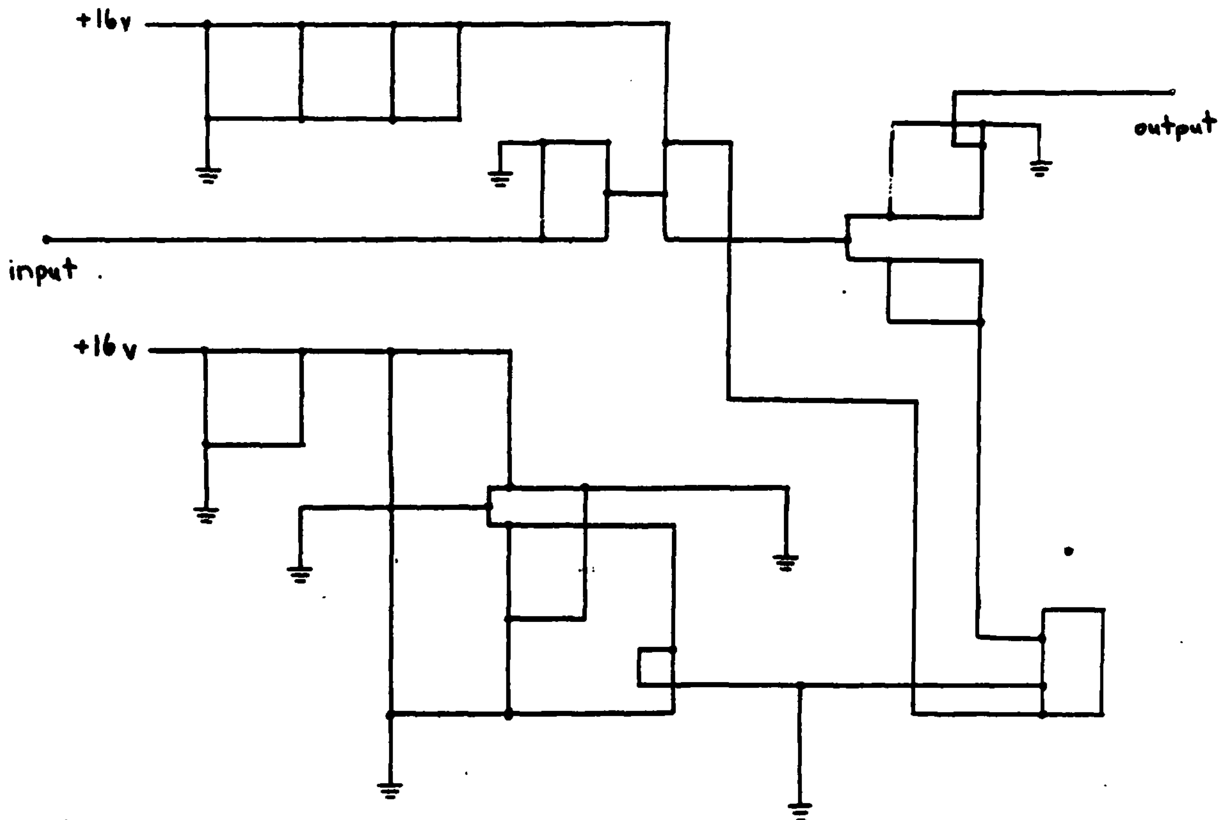

FIGURE 5.
THE MEDIUM-SIZED CIRCUIT OF FIGURE 2
(CONNECTIONS-ONLY FORMAT).

Procedure

Each subject participated in the experiment individually. The procedure was divided into several phases, which were carried out in either two or three sessions depending upon the expertise of the subject. The proficient subjects worked with the small and medium sized circuits, whereas the expert subjects worked with the medium-sized and large circuits. Trials on the two circuits on which a given subject was working (small and medium, or medium and large) were alternated, so that two tasks were in progress simultaneously. Each task thus provided short-term memory interference for the other.

Learning the Diagrams. In the learning or acquisition phase of the experiment, each subject was asked to reconstruct several circuit layouts for each of the two circuits to be worked on by that subject. To facilitate learning, these reconstructions were carried out from successively more and more impoverished versions of the diagrams. The subject first was presented with one layout of a diagram, in its complete format and was given a brief explanation of the circuits function and operation. The descriptions of the circuits presented in the Materials section above were read to the subject while the experimenter pointed to the particular parts of the diagram as they were mentioned. Then, with the complete diagram in view, the subject duplicated the circuit by placing the magnetic components on the lines-only format of the diagram in the identical layout. This procedure was completed for two different layouts of each of the two circuits, alternating between the circuits with which the subject was working.

Following this initial familiarization procedure, the complete diagrams were removed from view and the subject was shown a dot format of one of the two circuits. The subject was asked to reconstruct the circuit from

memory by placing the magnetic components on the layout. More components of each type were available than actually needed. When the subject finished, the experimenter recorded any errors of placement or omissions. Then, the subject was given a copy of the complete circuit and was instructed to correct any errors. This procedure was repeated, with alternating trials on each of the two circuits, until two different layouts had been completed.

Finally, the subject was asked to reconstruct each of the two circuits from memory using layouts that showed only the circuit connections, thus lacking specific indications of where the components were located. This portion of the procedure was repeated, using different layouts and alternating between circuits, until two completely correct reconstructions were achieved for each circuit. Errors in component placement and the number of trials to learn each circuit were recorded.

First Component Partitioning Task. After the initial acquisition phase of the experiment was completed, the subject was given a copy of the diagram in a layout not seen before and a set of colored pencils. The subject was asked to circle and identify the circuit components that go together, using different colors to indicate the degree to which components went together (see Table 1 for the colors and verbal codes). The task was introduced by an example which illustrated (1) the use of the different colors to designate various degrees of component relatedness, and (2) that a single component can participate in several different clusters at the same time, not necessarily overlapping. The data collected in this phase consisted of the participants' partitionings of the diagrams.

Reconstruction Trials. The general procedure in the reconstruction phase of the experiment was to have the subject perform five additional

TABLE 1

COLOR CODED SCALE FOR USE IN THE PARTITIONING TASK

SCALE VALUE	DESCRIPTIVE PHRASE	COLOR CODE
7	Inseparably related	Violet
6		Blue
5		Green
4	Moderately related	Yellow
3		Orange
2		Red
1	Weakly related	Brown

reconstructions of the two circuits. The connections-only layouts were rotated across trials, alternating between the two circuits. This time, the experimenter recorded the order in which the components were placed on each layout.

To achieve a variety of orders, four of the five trials on each circuit were begun with the experimenter placing one component on the layout. On these cued reconstruction trials, the subject was told:

> "I'm going to put one piece down first. You should reconstruct the circuit as before, but start by building out from the piece I put down. You do not have to make every piece connect to that one, but generally you should start building from that part of the diagram and complete that part first."

For each circuit, two different cue locations were selected and they were used twice during the experiment. These components are designated by asterisks in Figures 1, 2, and 3.

Second Component-Partitioning Task. At the end of the series of reconstructions, the component partitioning task was repeated, exactly as before. This repeat procedure was included to measure the extent to which the understanding of tne diagram had changed during the reconstruction phase.

Subjects

Eight subjects participated in this experiment, of which seven were classified as proficients. All subjects had recently obtained a B.S. degree in electrical engineering with at least one course in analog radio circuits and some post-bachelor experience with electrical circuits. Four of these subjects were enrolled as graduate students in electrical

engineering during the time of the experiment, and each had taken an advanced class in circuit theory. The subject that was classified as an expert had both technical training (the equivalent of a Master's degree in electrical engineering) and an appreciable amount of actual experience in designing and maintaining electronic equipment. The subjects were first classified by experience: the one advanced subject was considered an expert; and the other seven were considered proficients. The proficient subjects were further classified as high or low proficient on the basis of two performance crite ia, total time to complete the experiment and total number of errors made during the experiment. These data are presented in Table 2. The total test time varied as a function of both how long the subject took to learn the circuits and to reconstruct the circuit layouts.

It is worthy of note in Table 2 that the error rates for high and low proficients differ more sharply with the medium-sized circuit that with the small circuit. This underscores the need to use sufficiently complex circuits in tasks of the type studied here. Otherwise, differences between skill levels may be obscured.

Method of Analysis

Reconstruction Data. The multitrial free recall data were analyzed using Reitman and Reuter's (1980) algorithm for creating "ordered trees." The design of the experiment was such as to give about six complete recall orders for each subject (including the two recalls that preceded the first circling task), of which four were cued and two were free. These six orders were analyzed using the Reitman-Reuter procedure and their structure extracted. This clustering procedure yields a tree-like rendition of a subject's mental representation of a knowledge base. In such a tree, the branches represent individual elements and the nodes

TABLE 2

TIME TO COMPLETE EXPERIMENT AND NUMBER OF ERRORS MADE LEARNING CIRCUIT FOR INDIVIDUAL SUBJECTS

GROUP	SUBJECT	TIME	ERRORS: SMALL CIRCUIT	ERRORS: MEDIUM CIRCUIT	ERRORS: LARGE CIRCUIT
Low Proficients	B.B.	5.00 hrs	3	32	-
	J.S.	8.25 hrs	15	109	-
	B.N.	6.00 hrs	3	17	-
	C.S.	4.75 hrs	0	27	-
	Average	6.00 hrs	5.25	46.25	-
High Proficients	D.T.	4.00 hrs	4	3	-
	D.R.	4.25 hrs	0	11	-
	I.K.	3.50 hrs	0	3	-
	Average	3.91 hrs	1.33	5.67	-
Expert	M.E.	7.15 hrs	-	6	11

represent clusters or chunks of elements that "go together." Generally, the closer a node is to the root of the tree, the less related are the elements which combine at that node.

The resulting trees in the present research can be illustrated in two ways: first, as the recall tree itself; and second, as a set of clusters that represent the nodes of the tree drawn on the circuit itself. Because the number of different recall orders that are used as input to the program influences the amount of complexity that is derived, it is important to compare these statistics primarily for subjects for which the same amount of data has been obtained.

Once the tree has been constructed, a number of quantitative measures can be derived from it. The most simple of these are the number of clusters in the tree and the depth to which these clusters are nested. Since the algorithm designates each cluster as recalled in a fixed or an arbitrary order, the proportion of clusters containing three or more elements that are recalled directionally gives a further indication of strength. A more comprehensive measure is obtained by calculating the number of possible recall orders (PROs) that are consistent with the tree as derived. For a tree of any substantial size, the PRO is quite large and so it is somewhat easier to interpret the logarithm of the PRO. The base-two logarithm is used here, so that the results can be interpreted as a measure of information uncertainty (e.g., Shannon & Weaver, 1949). Large values of this statistic indicate that the recall orders show little consistent patterning, while small values indicate a large degree of consistency.

Partitioning Data. The analysis strategy was to use the ADCLUS model of Arabie and Carroll (1980) to covert the partitionings into a set of proximity matrices, and then to use various other scaling techniques to

reconstruct a pooled order from these. The circles marked by the subjects on the diagrams were converted to proximity matrices by a direct application of the ADCLUS-type weighting model. For each pair of components, the proximity between the components was calculated by summing the weights associated with all circles that contained both components. Thus, if two components were contained both in a red and a green circle (weights 2 and 5, respectively), then a proximity of 2 + 5 = 7 was assigned to the pair. By averaging over any set of partitioning, a pooled proximity matrix was obtained. In particular, the circling data for the subjects at various levels of skill were combined into a single proximity matrix.

Because the underlying structure of the mental representation was expected to involve a number of parallel hierarchies, it made most sense to analyze the partitioning data using a procedure that allows overlapping clusters to be extracted. Programs for this type of clustering exist and they were applied here in both two-mode and a three-mode manner (e.g., the ADCLUS procedure in Sarle, 1981).

RESULTS

The results are presented in terms of errors made during the learning phase of the experiment, recall orders from the reconstruction tasks, and partitioning clusters from the partitioning task.

Errors During Acquisition

The average number of errors made by the subjects in the initial reconstruction and learning of the circuits is shown in Table 3. Errors are categorized by the type of circuit element and they are averaged over ability group. Three characteristics are apparent in the data. First,

TABLE 3
MEAN ERRORS DURING LEARNING OF CIRCUIT

	CIRCUIT COMPONENT				
	Resistor (R)	Capacitor (C)	Transistor or Diode (Q)	Inductor (L)	TOTAL
SMALL CIRCUIT					
Low Proficients	1.8	1.2	0.0	2.2	5.2
High Proficients	0.7	0.7	0.0	0.0	1.3
MEDIUM CIRCUIT					
Low Proficients	11.5	18.2	7.8	10.8	48.2
High Proficients	1.7	2.0	0.7	1.3	5.7
Expert	1	4	0	1	6
LARGE CIRCUIT					
Expert	9	0	5	0	11

the number of errors is considerably smaller for the more experienced subjects, as would be expected. Second, the proportional distribution by circuit component type is similar at all levels of circuit difficulty. Finally, the number of errors in learning the circuit is very low for the best qualified subjects. Diagrams of this complexity are not hard to learn for subjects familiar with the circuits. However, this high-level of performance makes it difficult to identify response patterns for these subjects.

Recall Orders

Several examples of trees generated from data for the small and medium circuits, are shown in Figures 7 and 8 and 10 through 12. These trees, derived from subjects with different degrees of ability, were chosen to illustrate the wide range of behavior that was observed. Labels for the components of the small circuit are provided in Figure 6. Figure 7 shows the tree-structure results from a low proficient subject on the small circuit. This tree shows less order than that from any other subject, with only one cluster appearing consistently across reconstructions. For this same circuit, Figure 8 shows a more proficient subject who provides a much higher degree of order. The corresponding diagrams for these subjects on the medium circuits are presented in Figures 10 and 11. Labels for the components of the medium circuit are provided in Figure 9. Here, both subjects have a fairly high degree of order. The final diagram (Figure 12) shows the clustering generated by the expert subject on the medium circuit. Most striking in Figures 6-12 is the high degree of inconsistency across the set of trees. Although the largest degree of within subject variability and of inconsistency across skill ranges is illustrated here, results from the other subjects are similar.

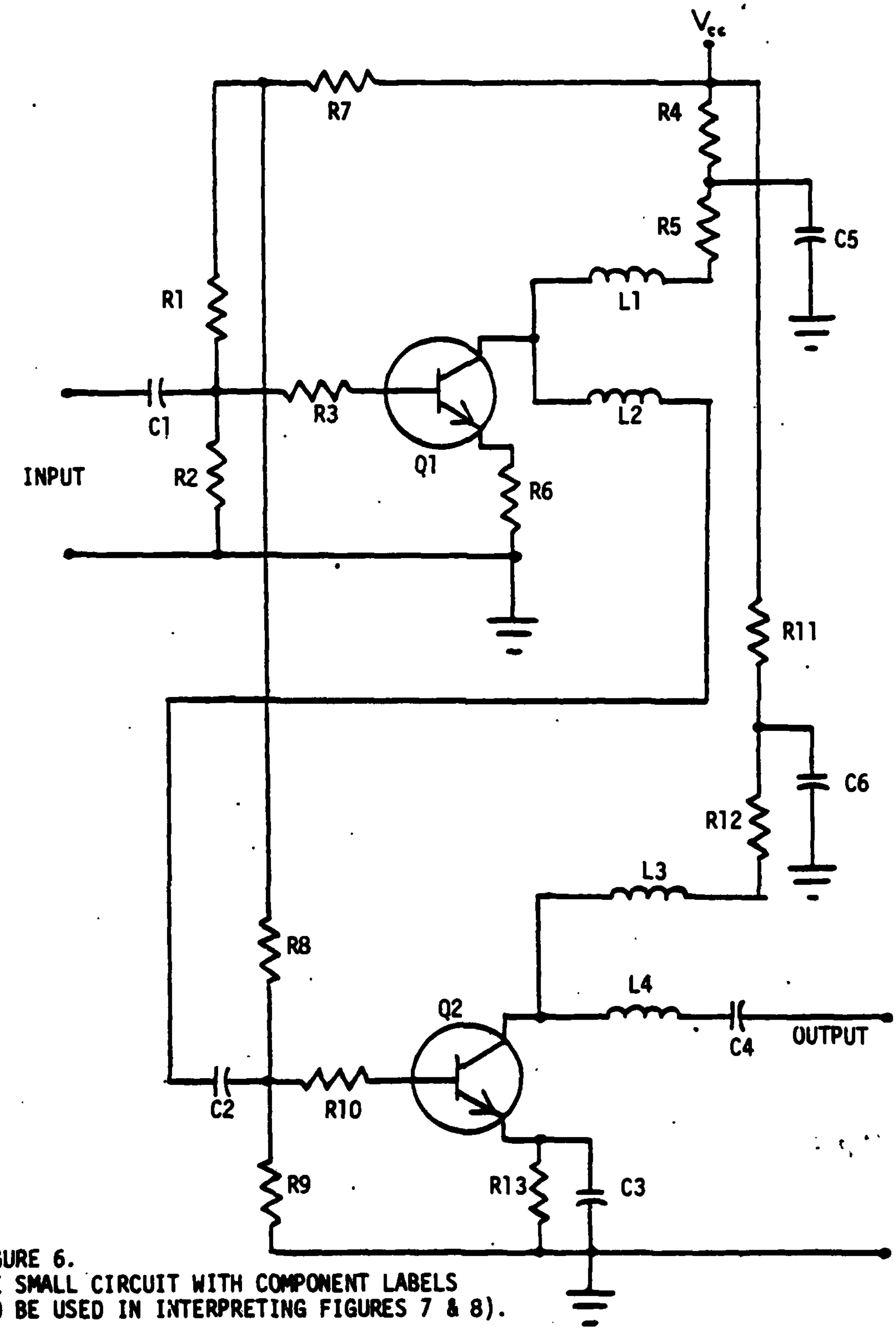

FIGURE 6.
THE SMALL CIRCUIT WITH COMPONENT LABELS
(TO BE USED IN INTERPRETING FIGURES 7 & 8).

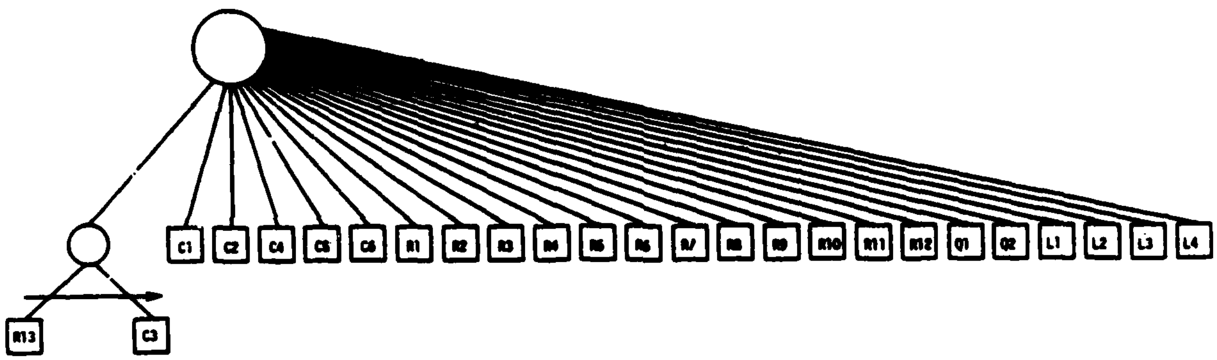

FIGURE 7.
TREE DIAGRAM OF THE REITMAN-REUTER SOLUTION FOR A LOW-PROFICIENT SUBJECT ON THE SMALL CIRCUIT (THE COMPONENT LABELS ARE PROVIDED IN FIGURE 6).

[Nodes = 2; PRO = 6.20×10^{23}; Log_2 PRO = 79.04]

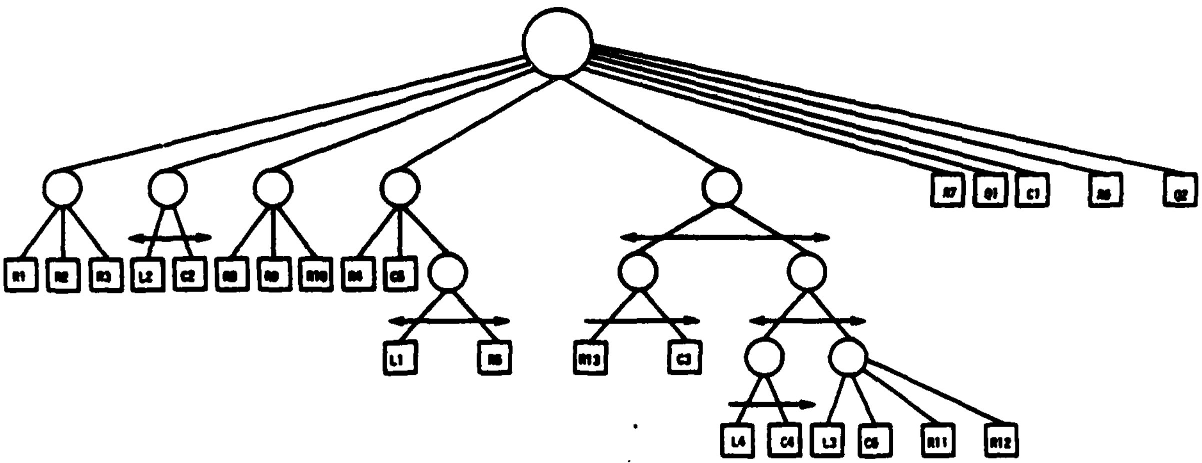

FIGURE 8.
TREE DIAGRAM OF THE REITMAN-REUTER SOLUTION FOR A HIGH-PROFICIENT SUBJECT ON THE SMALL CIRCUIT (THE COMPONENT LABELS ARE PROVIDED IN FIGURE 6).

[Nodes = 11; PRO = 3.01×10^{11}; Log_2 PRO = 38.13]

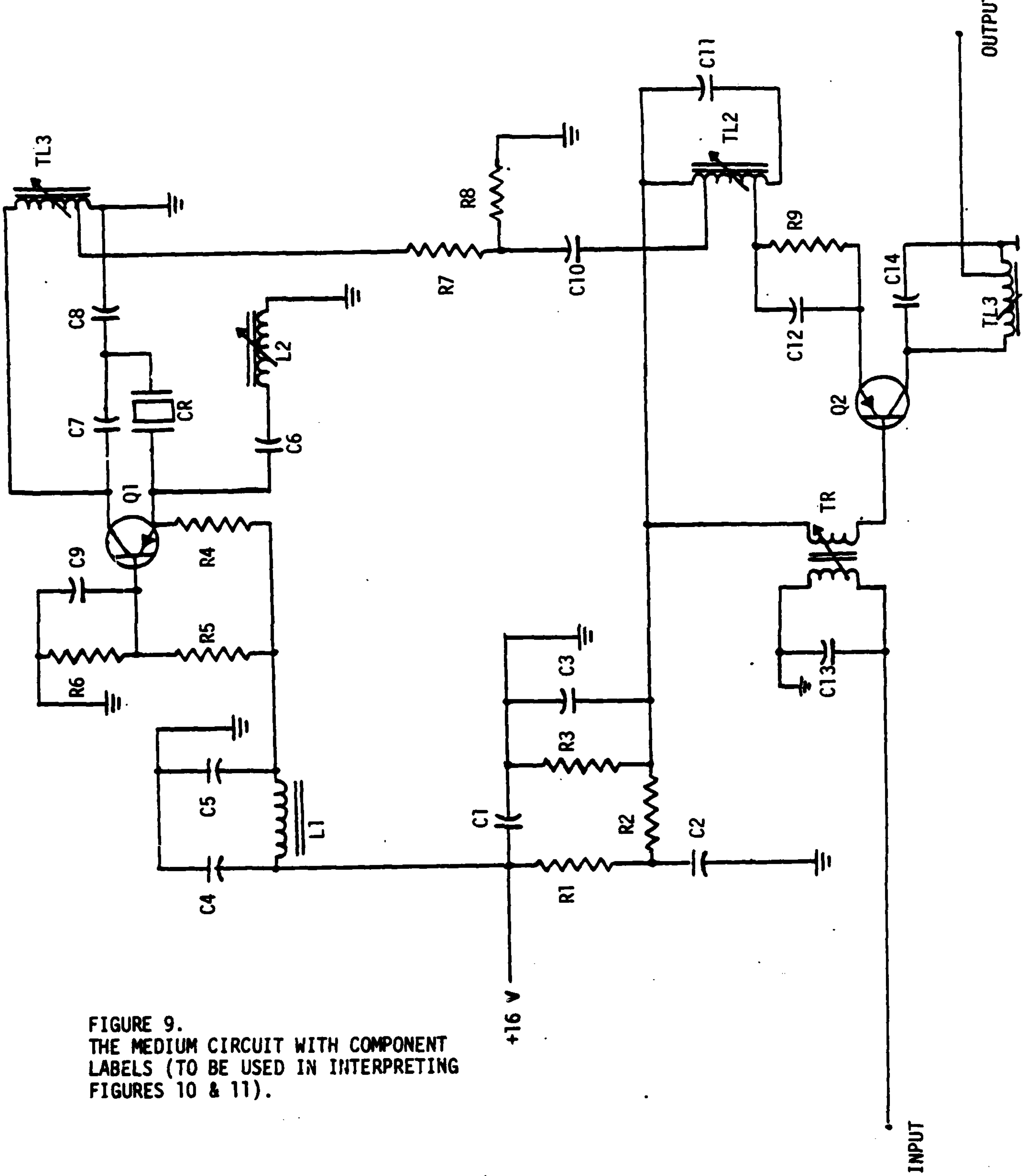

FIGURE 9.
THE MEDIUM CIRCUIT WITH COMPONENT LABELS (TO BE USED IN INTERPRETING FIGURES 10 & 11).

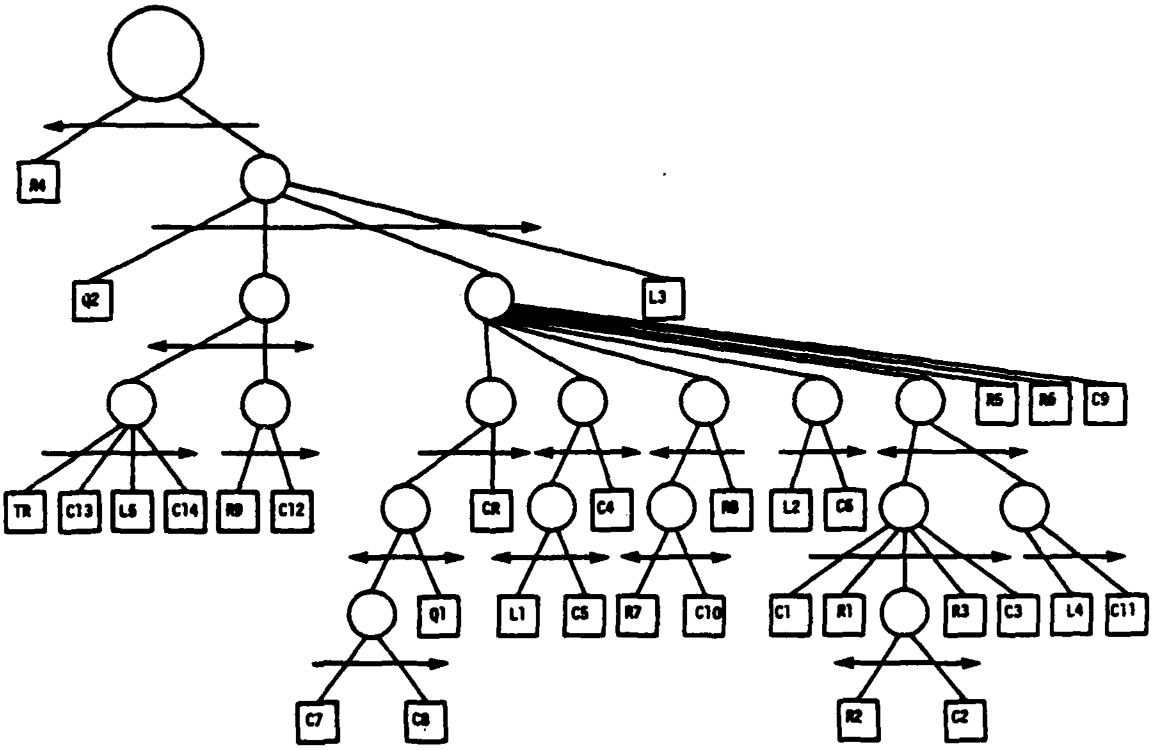

FIGURE 10.
TREE DIAGRAM OF THE REITMAN-REUTER SOLUTION FOR A LOW-PROFICIENT SUBJECT ON THE MEDIUM CURCUIT (THE COMPONENT LABELS ARE PROVIDED IN FIGURE 9).

[Nodes = 18; PRO = 2.58×10^6; Log_2 PRO = 21.30]

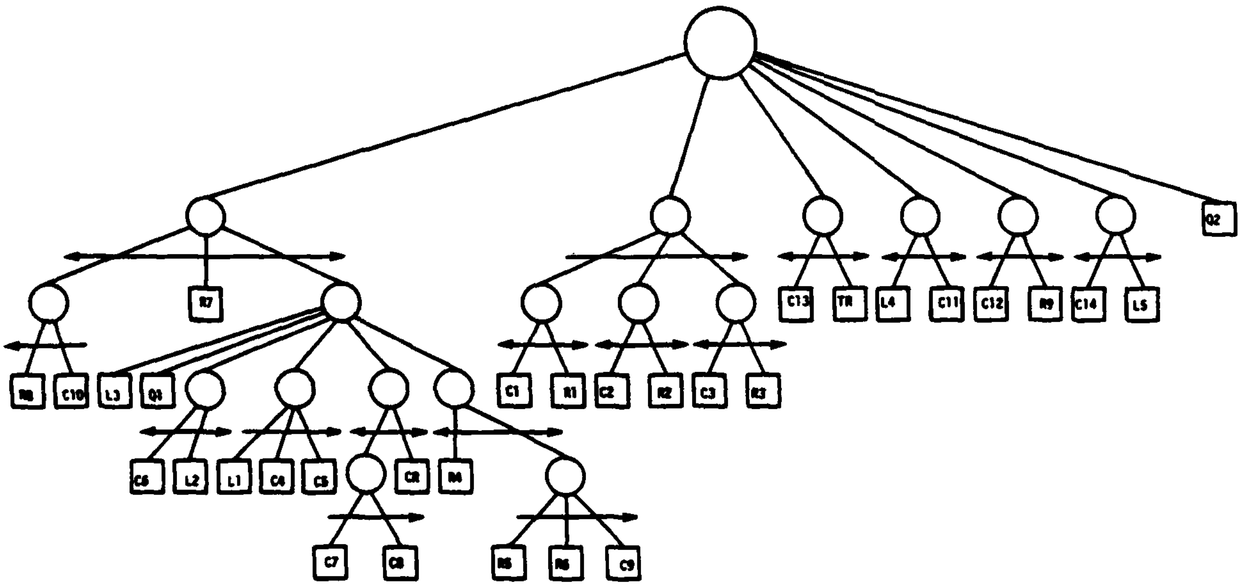

FIGURE 11.
TREE DIAGRAM OF THE REITMAN-REUTER SOLUTION FOR A HIGH-PROFICIENT SUBJECT ON THE MEDIUM CIRCUIT (THE COMPONENT LABELS ARE PROVIDED IN FIGURE 9).

[Nodes = 18; PRO = 1.475×10^6; Log_2 PRO = 20.49]

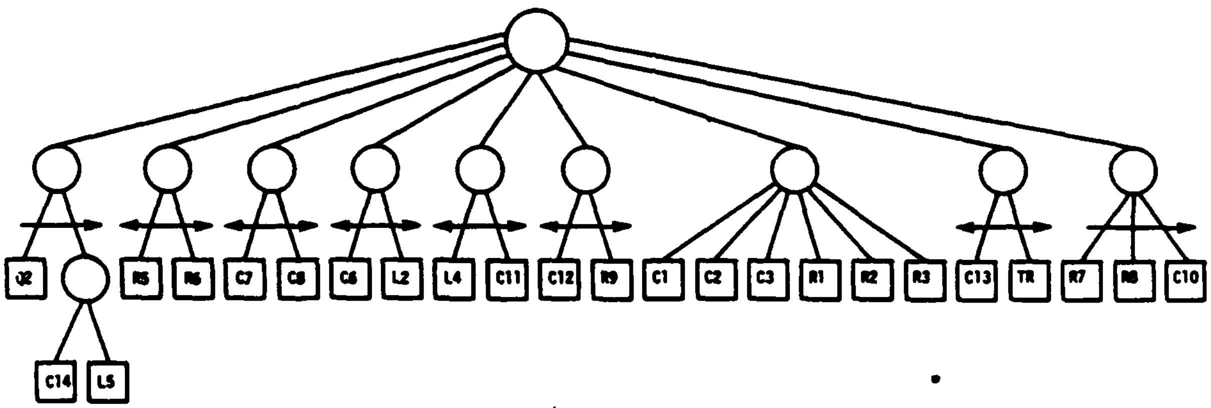

FIGURE 12.
TREE DIAGRAM OF THE REITMAN-REUTER SOLUTION FOR THE EXPERT SUBJECT ON THE MEDIUM CIRCUIT (THE COMPONENT LABELS ARE PROVIDED IN FIGURE 9).

[Nodes = 11; PRO = 9.216×10^4; Log_2 PRO = 16.477]

TABLE 4

SUMMARY STATISTICS FOR TREES RECOVERED
BY REITMAN-REUTER ALGORITHMS

Measure	Low-Proficient Subjects Range	Low-Proficient Subjects Mean	High-Proficient Subjects Range	High-Proficient Subjects Mean
SMALL CIRCUIT				
No. of Clusters	1-10	4.2	5-10	7.0
Average Size	2.0-2.8	2.4	2.0-3.6	2.6
Maximum Levels	1-2	1.5	1-3	1.5
Log_2PRO	31.0-79.0	65.3	38.1-64.1	54.65
MEDIUM CIRCUIT				
No. of Clusters	8-17	11.8	10-17	12.7
Average Size	2.3-5.4	3.4	2.4-4.1	3.0
Maximum Levels	2-5	3.0	2-4	2.7
Log_2PRO	21.3-72.7	52.4	20.5-74.0	53.1

Summary statistics for the trees are shown in Table 4; again most striking is the degree of similarity in average performance between the high and low-proficient groups. No differences among the measures reached statistical significance. While it is possible that with a considerably larger group of subjects, some reliable differences would be found, it is apparent that they would be relatively small in comparison with the variability in performance within the skill levels.

Partition Clusters. The data obtained in the partitioning task were first pooled over both circlings for each subject and for all subjects within an ability level, creating two matrices for each diagram. These were first scaled alone, and then in a three-mode manner to extract common clusters. These clusterings are shown in Figures 13-15 and 16-18 for the small and medium circuits, respectively. The first figure in each set shows the clusters recovered from the data of the low-proficient subjects. The second shows the same data for the high-proficient subjects, and the last shows the results of a three-mode analysis based on both sets of data. Each cluster is labeled with the percentage of the total variance of the proximities that could be accounted for by that cluster.

Figure 13 shows the four clusters that accounted for the largest amount of variance (73% in all). Two clusters correspond to the two amplifier stages of the circuit, the other two clusters block all except the output portions of the same groups. The full clustering solution for this diagram contained other clusters as well, but these accounted for relatively small amounts of the variance and they have not been plotted here. Figure 14 shows a similar diagram for the high-proficient subjects, and three of the clusters are similar to those in Figure 13. The remaining cluster in Figure 14 puts together the output filters of both stages, illustrating the clustering of components by similar functioning

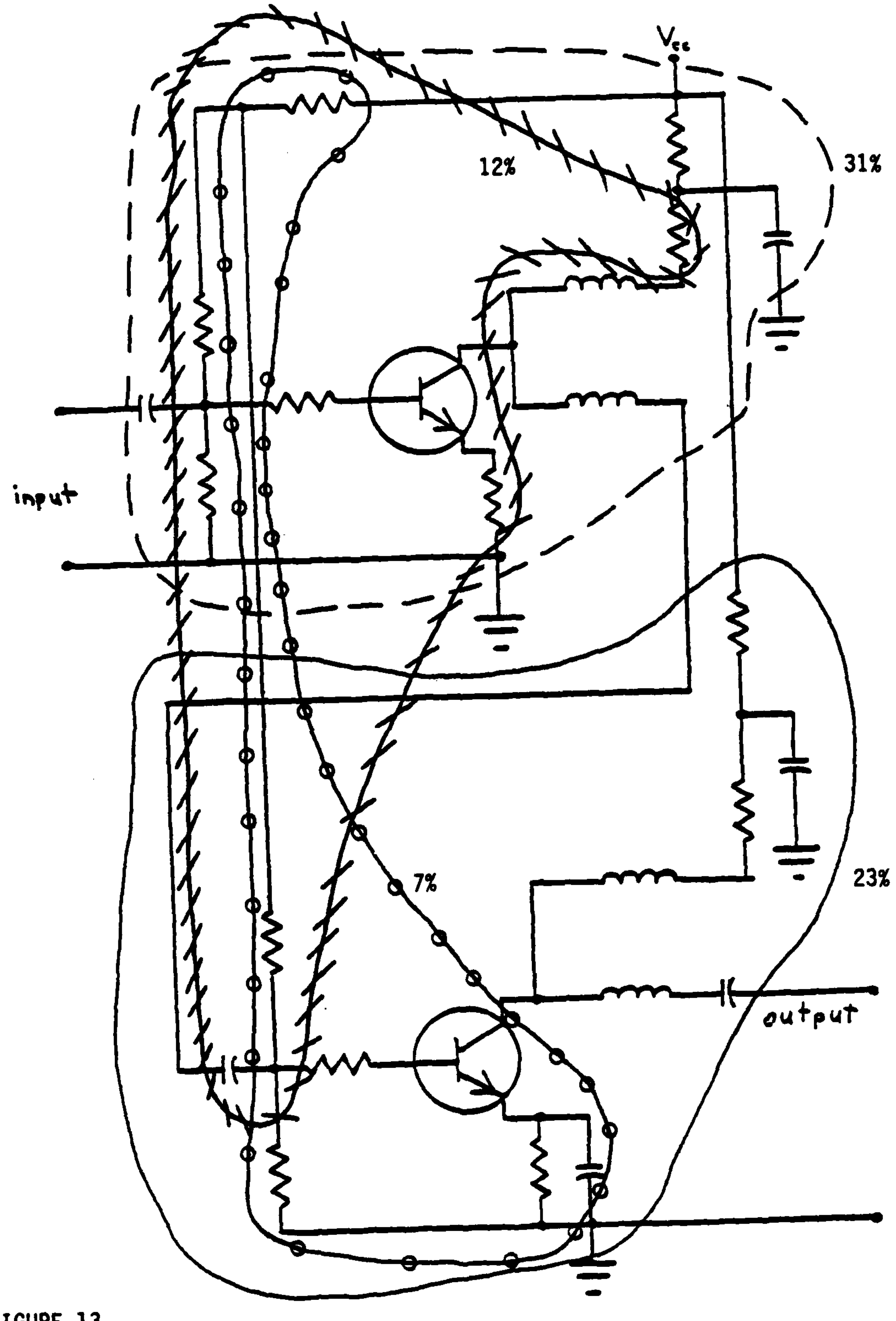

FIGURE 13.
ADCLUS SOLUTION FOR THE SMALL CIRCUIT, LOW-PROFICIENT SUBJECTS.

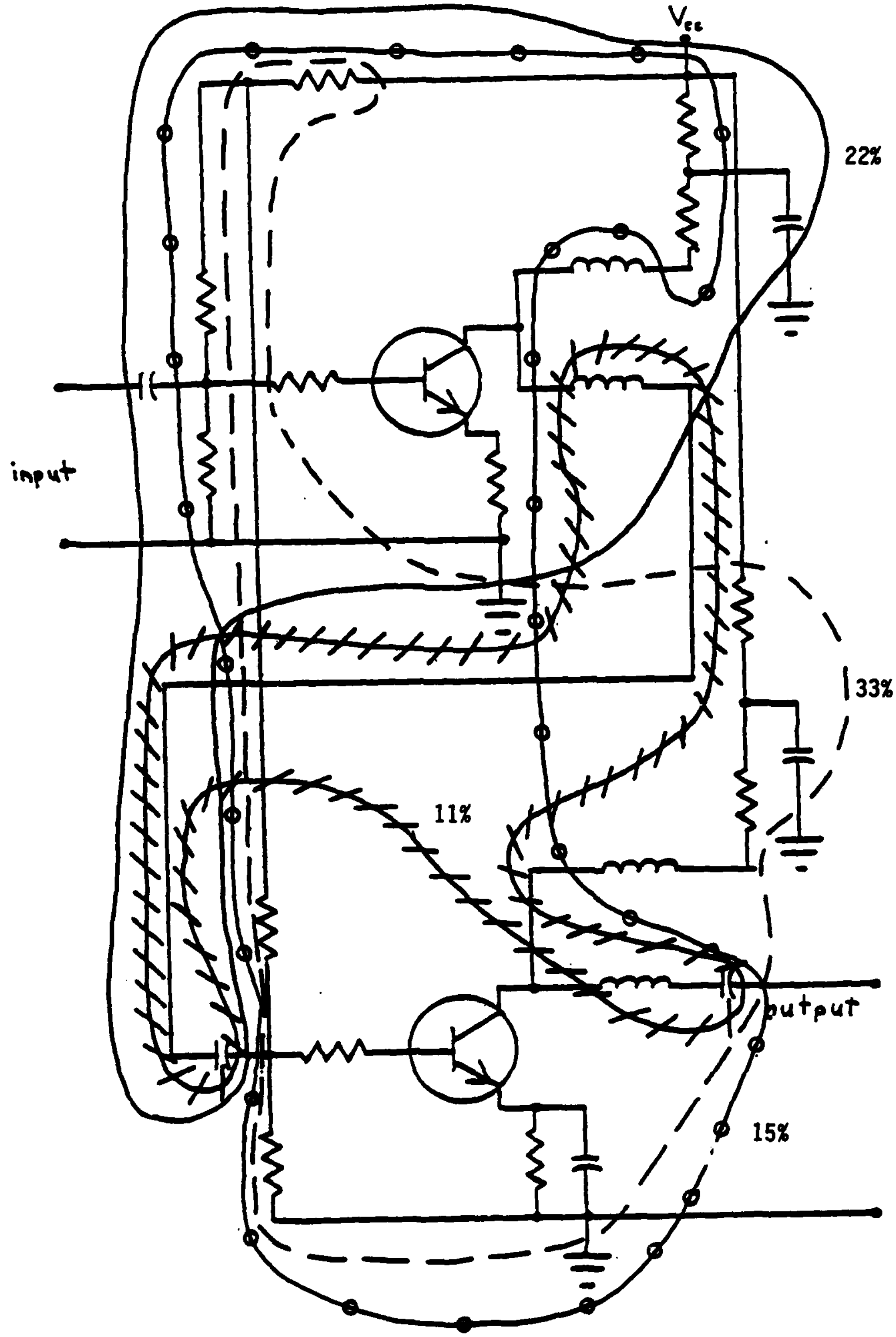

FIGURE 14.
ADCLUS SOLUTION FOR THE SMALL CIRCUIT,
HIGH-PROFICIENT SUBJECTS.

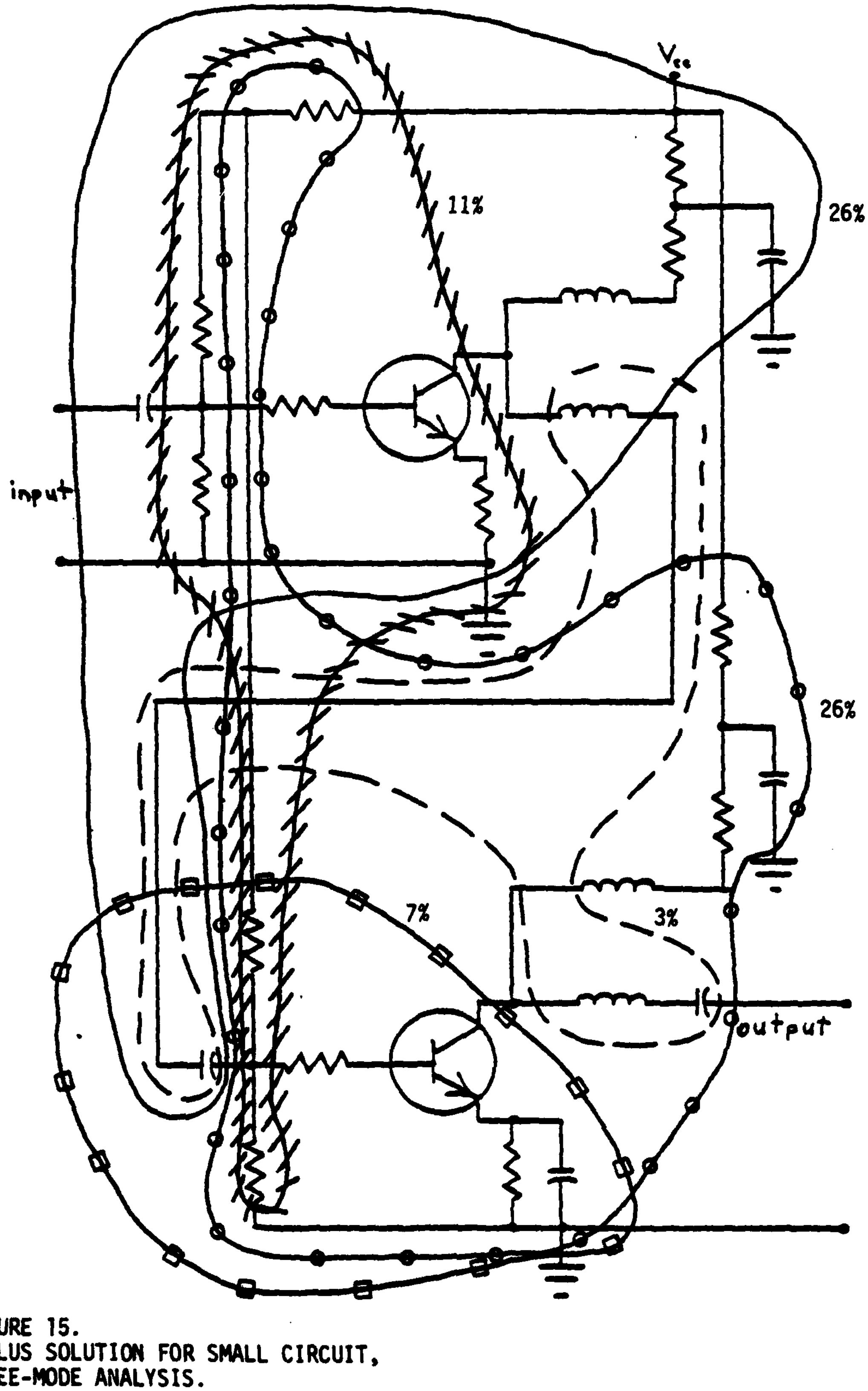

FIGURE 15.
ADCLUS SOLUTION FOR SMALL CIRCUIT, THREE-MODE ANALYSIS.

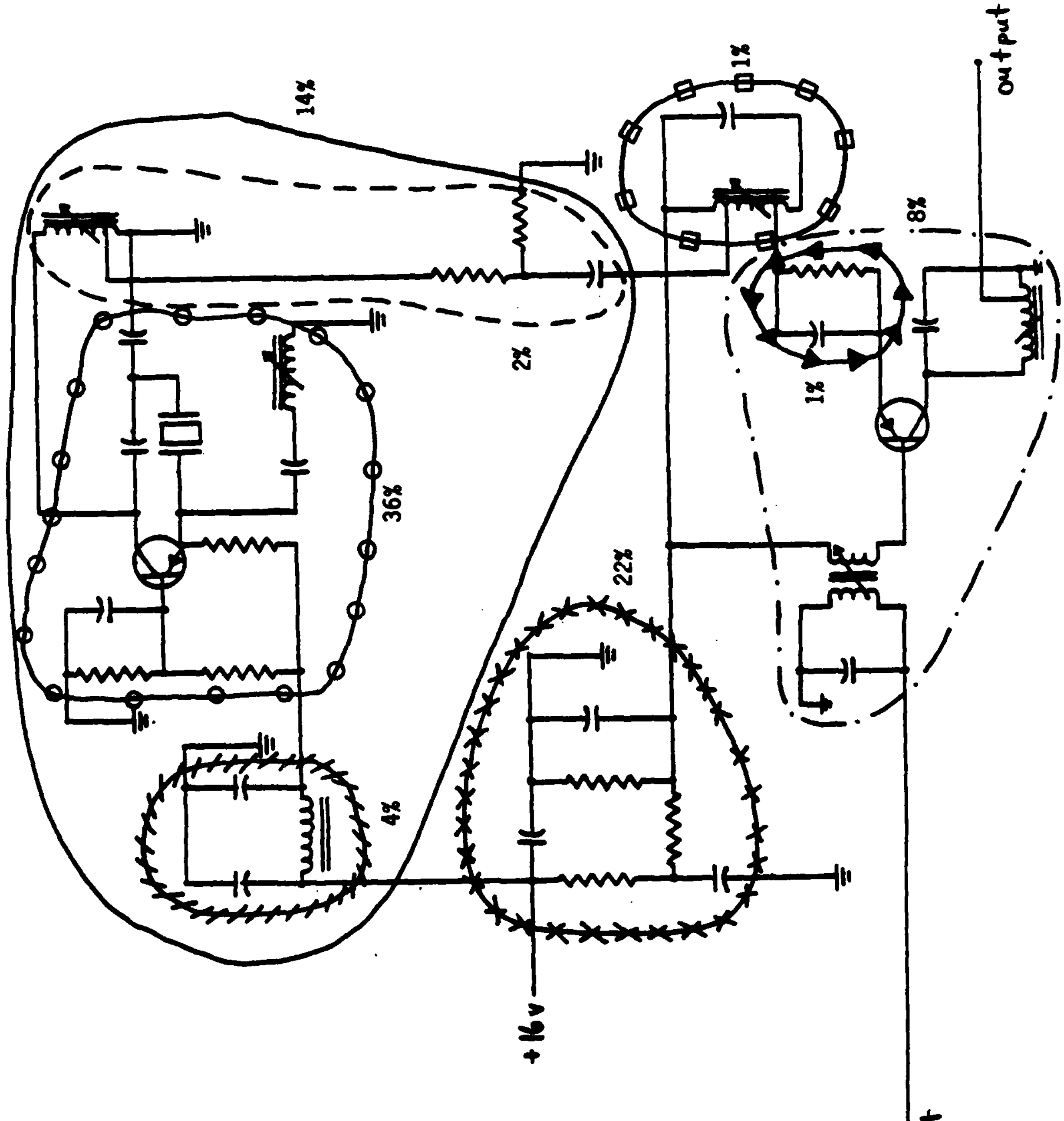

FIGURE 16.
ADCLUS SOLUTION FOR THE MEDIUM CIRCUIT,
LOW-PROFICIENT SUBJECTS.

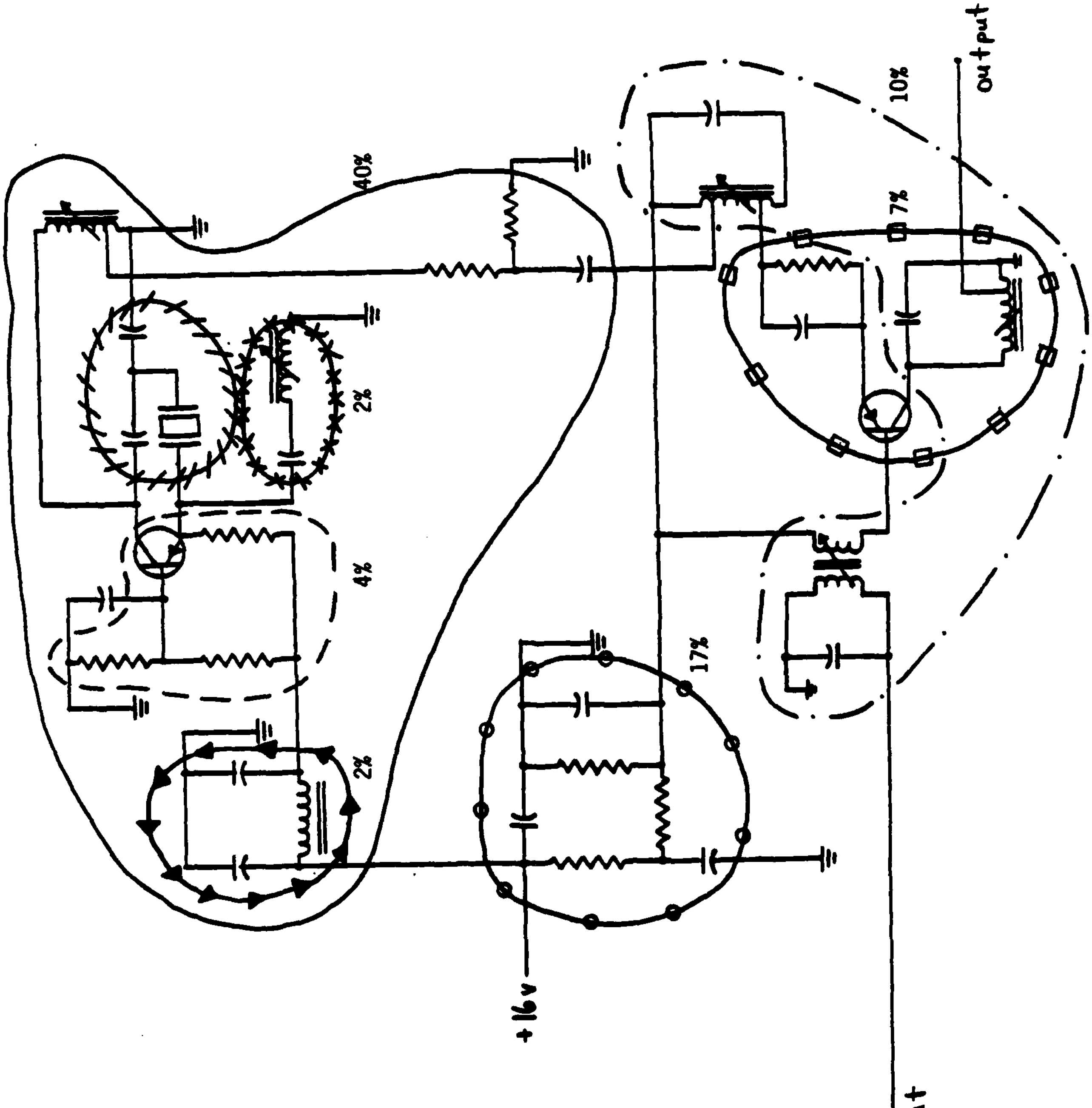

FIGURE 17.
ADCLUS SOLUTION FOR THE MEDIUM CIRCUIT,
HIGH-PROFICIENT SUBJECTS.

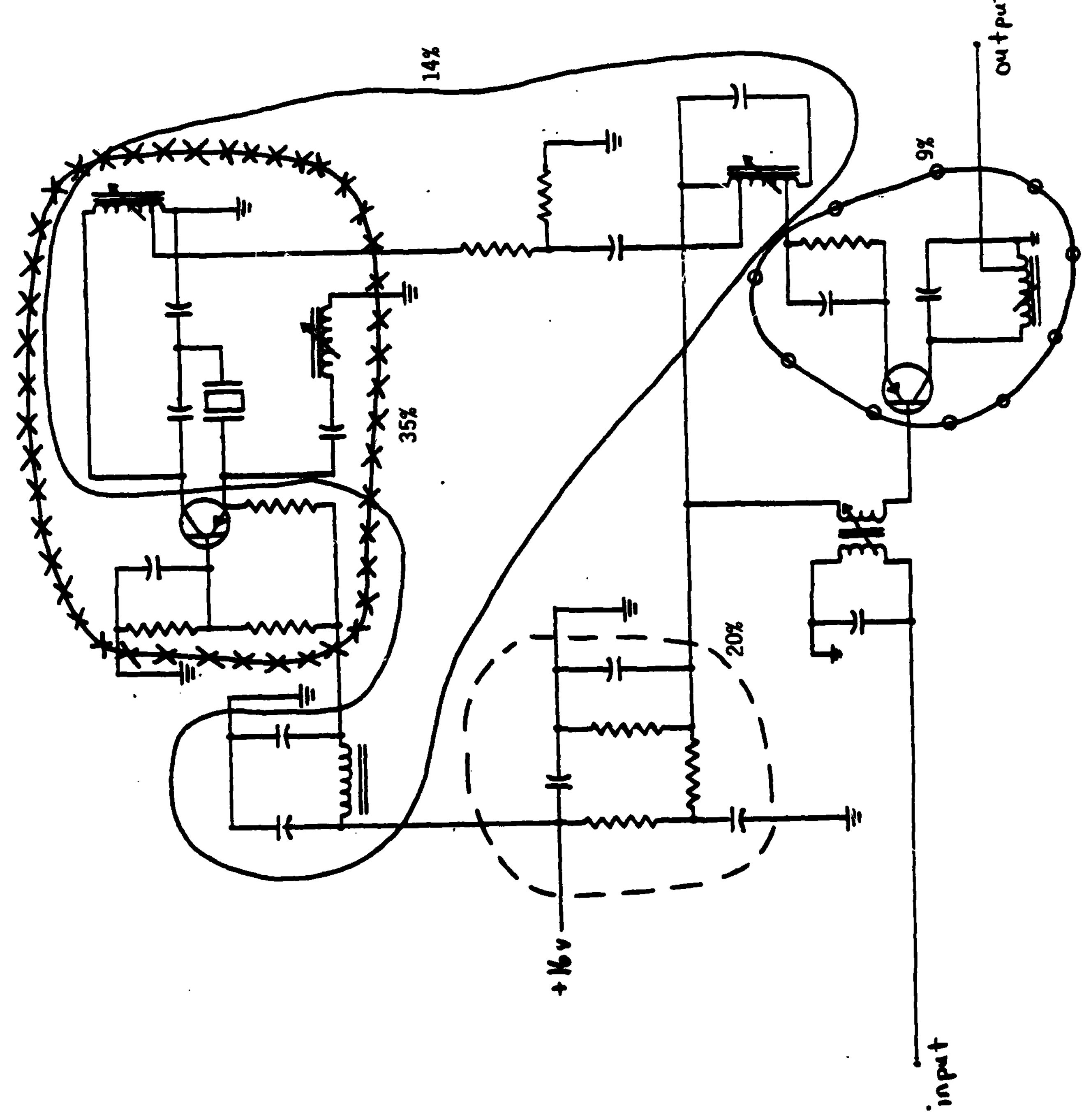

FIGURE 18.
ADCLUS SOLUTION FOR THE MEDIUM CIRCUIT,
THREE-MODE ANALYSIS.

in a way that cuts across component type or physical proximity. Figure 15 shows the same data scaled in a three-mode manner, so that clusters are selected that are based on either group's responses. With a few differences, this solution roughly reproduce the patterns that were seen for the individual group solutions.

The clustering of the medium circuit is illustrated in Figures 16-18. Overlapping clusters are less prevalent here than with the small circuit. The most reliably clustered components are those that were involved in the oscillator portion of the circuit. Because of the weighting of the original clusters, a reliably, but low-weighted cluster can have small explained variance in the ultimate solution. Several such low-variance clusters are included in the single-group diagrams.

The clusters in Figures 13-18 do not necessarily reproduce clusters that appeared in the clusters generated by individual subjects. When several subjects circle similar, but not identical groups of components, the scaling procedure generates clusters that show the union and the intersection of the clusters. For example, if three subjects circled the sets of components (a,b,c,d), (b,c,d,e), and (a,c,d,e), then the full set would show one level of proximity, and the two elements in the intersection would be represented on a higher level. The result of this scale would give the double cluster [a,b,(c,d),e]. The most obvious place where this phenomenon appears to have happened is with clusters 2 and 3 of Figure 16.

DISCUSSION

The principal finding evident from the data presented here is the large degree of variability in the performance among the subjects on the reconstruction and cluster-generating tasks, and the extent of overlap

between the different ability groups on those tasks. These data stand in contrast to the relatively large differences between skill levels that appear in the time and error measures with respect to overall performance (Tables 2 and 3). The size of the subject samples are too small to apply statistical tests to data such as those summarizing the Reitman-Reuter trees in Table 4, but it is clear that within-group variability on those performance measures are larger than the between-group differences. Even if a large sample could provide statistically significant differences between skill levels, the size of the effect as a proportion of variability would probably not be very great. This conclusion is all the more apparent from a comparison of the within-subject variation in performance on the small medium circuits (Figures 7 and 8 compared to Figures 10 and 11, respectively, provide a particularly striking example).

The Reitman-Reuter procedure, as applied here, is highly sensitive to changes in recall order; that is, where recall orders are different, the procedure infers no structure at all. Thus, the use of circuit diagrams that were constrained by their physical layout may have imposed a varied structure on recall order from trial to trial. These constraints, by necessities of the experimental design, differed from layout to layout and may have served to alter the recall orders sufficiently so as to weaken the results. Although the Reitman-Reuter procedure is potentially useful for analyzing performance on reconstruction tasks of this sort, it would probably be more valuable when applied to situations in which full free recall is used.

Nevertheless, there are a few places where performance differences between different ability groups do, in fact, appear. First, as the original basis for the skill-level division shows, there are substantial differences in the speed and accuracy measures for learning and recon-

structing the diagrams (Tables 2 and 3). Additionally, in some instances, differences in the tree structures and clusterings showed the emergence of a different type of circuit organization for the better subjects (see, particularly, the results for the partitioning tasks--Figures 13 through 18). The relatively small size of these effects and the large variance of the measures suggest, however, that the investigation of structural/functional knowledge with respect to these type of circuit diagrams is not the most productive place for further research effort.

Hence, identifiable, differences in the organization of a diagram during learning and recall do not appear to be the most sensitive loci of proficiency differences. For reasonably simple and well-learned material, the physical properties of the diagram layout may dominate performance. It is conceivable that differences could appear between subjects of different proficiency levels, with the less proficient subjects being more bound by the physical construction of the target circuit, and the more proficient subjects being more bound by the logical construction. In conventionally well-drawn circuit diagrams, however, these two organizations coincide, minimizing differences in performance.

In contrast, more substantial differences are more likely to appear in the way in which the circuit diagrams are manipulated, that is, in operations that are performed on the diagrams. Even with improperly drawn diagrams, where the logical and physical aspects conflict, the expert's advantage would come through an ability to reorganize the circuit. Thus, the principal performance differences between the most skilled and least skilled subjects may be a result of differences in their respective levels of procedural knowledge. For this reason, the next phase of this work will examine performance on tasks that require technicians to manipulate circuits in prescribed ways. Such research,

focusing on the investigation of procedural knowledge, will complement the present exploration of individual differences in structural/functional knowledge.

REFERENCES

Anderson, J.R. Language, memory and thought. Hillsdale, N.J.: Erlbaum, 1976.

Anderson, J.R., & Bower, G.H. Human associative memory. Washington, D.C.: Winston, 1973.

Arabie, P., & Carroll, J.D. MAPCLUS: A mathematical approach to fitting the ADCLUS model. Psychometrika, 1980, 45, 211-235.

Badre, A.M. Selecting and representing information structures for battlefield decision systems. (Report No. TR-79-A20.) Alexandria, VA: U.S. Army Research Institute for the Behavioral and Social Sciences, June 1979.

Bhaskar, R., & Simon, H.A. Problem solving in semantically rich domain: An example from engineering thermodynamics. Cognitive Science, 1977, 1, 139-215.

Bond. N.A., & Towne, D.M. Troubleshooting complex equipment in the military services: Research and prospects (Technical Report 92). Los Angeles: University of Southern California, Behavioral Technology Laboratories. December 1979.

Brown, J.S., Collins, A., & Harris, G. Artificial intelligence and learning strategies. In H.F. O'Neil, Jr. (Ed.), Learning Strategies. New York: Academic Press, 1978.

Chase, W.G., & Simon, H.A. Perception in chess. Cognitive Psychology, 1973, 4, 55-81.

Chi, M., Feltovich, P., & Glaser, R. Physics problem solving by experts and novices. Paper presented at the Twentieth Annual Meeting of the Psychonomic Society, Phoenix, November 1979.

Collins, A.M., & Loftus, E.G. A spreading-activation theory of semantic processing. Psychological Review, 1975, 82, 407-428.

DeGroot, A.D. Perception and memory versus thought: Some old ideas and recent findings. In B. Kleinmuntz (Ed.), Problem solving: Research, method, and theory. New York: Wiley, 1966.

DeKleer, J. Casual and teleological reasoning in circuit recognition. (AR-TR-529.) Cambridge, MA: Artificial Intelligence Laboratory, Massachusetts Institute of Technology, September 1979.

DeKleer, J., & Brown, J.S. Mental models of physical mechanisms and their acquisition. Unpublished manuscript, 1980. (Available from XEROX PARC, Cognitive and Institutional Sciences, 3333 Coyote Hill Road, Palo Alto, CA, 94304.)

Egan, D.C., & Schwartz, B.J. Chunking in recall of symbolic drawings. Memory and Cognition, 1979, 7, 149-158.

Greeno, J.G. Natures of problem-solving abilities. In W.K. Estes (Ed.), Handbook of learning and cognitive processes. Volume 5: Human information processing. Hillsdale, NJ: Erlbaum, 1978.

Larkin, J.H. Expertise and solution strategies for textbook physics problems. Paper presented at the Twentieth Annual Meeting of the Psychonomic Society, Phoenix, November 1979.

Larkin, J.H., McDermott, J., Simon, D.P., & Simon, H.A. Models of competence in solving physics problems. Cognitive Science, 1980, 4, 317-345.

Newell, A., & Simon, H.A. Human problem solving. Englewood Cliffs, NJ: Prentice-Hall, 1972.

Norman, D.A., & Rumelhart, D.E. (Eds.) Explorations in cognition. San Francisco: W.H. Freeman, 1975.

Reitman, J. Skilled perception in Go: Deducing memory structures from inter-response times. Cognitive Psychology, 1976, 6, 336-356.

Reitman, J.S., McKeithen, K.B., Reuter, H.R., & Hirtle, S. Knowledge organization of expert and novice programmers. Paper presented at the Twentieth Annual Meeting of the Psychonomic Society, Phoenix, November 1979.

Reitman, J.S., & Reuter, H.H. Organization revealed by recall orders and confirmed by pauses. Cognitive Psychology, 1980, 12, 554-581.

Sarle, W.S. The ADCLUS procedure (SAS Technical Report No. S-124). Cary, N.C.: SAS Institute, 1981.

Schank, R.C. Conceptual dependency: A theory of natural language understanding. Cognitive Psychology, 1972, 3, 553-631.

Shannon, C.E., & Weaver, W. The mathematical theory of communication, Urbana, IL: University of Illinois Press, 1949.

Simon, H.A., & Chase, W.G. Skill in chess. American Scientist, 1973, 61, 394-403.

Simon, H.A., & Gilmartin, K. A simulation of memory for chess positions. *Cognitive Psychology*, 1973, *5*, 29-46.

Winograd, T. A program for understanding natural language. *Cognitive Psychology*, 1972, *3*, 1-191.

ATE

ME